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PRACTICAL TOOLS

Conservation, Ecology and Artificial Intelligence: Advances and Symbiotic Solutions

WildWing: An open-source, autonomous and affordable UAS for animal behaviour video monitoring

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Abstract

1. Drones have become invaluable tools for studying animal behaviour in the wild, enabling researchers to collect aerial video data of group-living animals. However, manually piloting drones to track animal groups consistently is challenging due to complex factors such as terrain, vegetation, group spread and movement patterns. The variability in manual piloting can result in unusable data for downstream behavioural analysis, making it difficult to collect standardized datasets for studying collective animal behaviour.
2. To address these challenges, we present WildWing, a complete hardware and software open-source unmanned aerial system (UAS) for autonomously collecting behavioural video data of group-living animals. The system's main goal is to automate and standardize the collection of high-quality aerial footage suitable for computer vision-based behaviour analysis. We provide a novel navigation policy to autonomously track animal groups while maintaining optimal camera angles and distances for behavioural analysis, reducing the inconsistencies inherent in manual piloting.
3. The complete WildWing system costs only $650 and incorporates drone hardware with custom software that integrates ecological knowledge into autonomous navigation decisions. The system produces 4K resolution video at 30 fps while automatically maintaining appropriate distances and angles for behaviour analysis. We validate the system through field deployments tracking groups of Grevy's zebras, giraffes and Przewalski's horses at The Wilds conservation centre, demonstrating its ability to collect usable behavioural data consistently.
4. By automating the data collection process, WildWing helps ensure consistent, high-quality video data suitable for computer vision analysis of animal behaviour. This standardization is crucial for developing robust automated behaviour recognition systems to help researchers study and monitor wildlife populations at scale. The open-source nature of WildWing makes autonomous behavioural data collection more accessible to researchers, enabling wider application of drone-based behavioural monitoring in conservation and ecological research.

KEYWORDS
animal ecology, autonomous drone, behaviour, Imageomics, unmanned aerial system, video monitoring

1 | INTRODUCTION

Drones have emerged as a powerful technology for studying animal behaviour, enabling researchers to collect aerial footage of wildlife in their natural habitats. By partnering human expertise with drone technology, researchers can dramatically expand their observational capabilities, gathering high-quality behavioural data across challenging terrains without the limitations of ground-based methods. The strategic application of this technology amplifies researchers' effectiveness, enabling them to collect comprehensive data sets while maintaining the careful approach needed for wildlife studies. These aerial perspectives allow researchers to simultaneously observe all individuals in a group (Schad & Fischer, 2023)—something impossible with traditional ground-based observation methods such as focal or scan sampling (Altmann, 1974). This comprehensive perspective is particularly valuable for understanding collective behaviour, where interactions between individuals and their environment shape group dynamics. Drones have already been used to study the behaviour of a wide variety of species in differing habitats, including African ungulates (Kholiavchenko et al.2024; Koger et al., 2023; Price et al., 2023), Przewalski's horse (Ozogány et al., 2023), baboons (Duporge et al., 2024), caribou (Torney et al., 2018), elephants (McNutt et al., 2024) and even underwater tracking of fish species (Cai et al., 2023).

The current state-of-the-art methodology for collecting aerial drone footage of wildlife behaviour relies on human pilots to fly the drone manually. However, manually collecting usable behavioural data with drones presents significant challenges in the field. Collective behaviour is challenging to capture, requiring fine-scale observations of multiple animals simultaneously (Hughey et al., 2018). Researchers must maintain optimal viewing angles and distances as animals move through complex terrain while ensuring that all individuals remain in the frame as groups spread out or merge. This task requires quick responses to sudden changes in group movement or direction, all while maintaining consistent data quality across multiple observation sessions and minimizing disturbance to the animals.

Manual drone piloting often fails to address these challenges adequately, and humans generally overestimate their ability to track moving targets. Recent research demonstrates that autonomous tracking systems outperform human pilots by 22% when following a single object moving faster than 2.5 m per second—approximately the speed of a walking horse (Bala et al., 2024). When this baseline difficulty is compounded by environmental factors such as vegetation occlusions, varying topography and the need to track multiple animals simultaneously, the challenge of recording group-living animals becomes far more complex than initially apparent. Human pilots must balance multiple cognitively demanding tasks simultaneously: tracking moving targets while adjusting altitude and position to maintain proper framing, navigating around landscape features and obstacles, monitoring battery levels and environmental conditions and complying with drone regulations and safety protocols. This cognitive burden of multitasking frequently results in inconsistent footage quality for downstream analysis. Video segments must be excluded from analysis when animals' species or behaviour cannot be identified due to insufficient image resolution or occlusion from vegetation. For example, the In-Situ Dataset for Kenyan Animal Behavior Recognition from Drone Videos (KABR) collected through manual piloting yielded only 65% usable data for behavioural analysis, despite requiring 3 weeks of fieldwork (Kholiavchenko et al., 2024). Such inefficiencies make building the comprehensive datasets needed for understanding collective behavior difficult.

An autonomous approach could help overcome the limitations of the current state-of-the-art manual approach. Autonomous drones can maintain consistent viewing angles and distances, react more quickly to group movements and produce more consistent, standardized data across sessions by automating the core tracking and positioning tasks. This automation allows human operators to focus on safety and research objectives rather than the technical demands of piloting. Autonomous drones can assist ecologists in monitoring and responding to complex, emerging collective animal behaviours that are beyond the abilities of a manual pilot. Autonomous drone missions are safer, more reliable and more consistent than manual missions (Boubin & Stewart, 2020). In addition, autonomous drone missions can be programmed with safety features to minimize animal disturbance, reduce crashes and ensure compliance with drone regulations.

Autonomous drones have been successfully deployed to locate individuals and estimate animals' positions (Andrew et al., 2020; Meier et al., 2024). However, autonomous tracking of wildlife remains largely unexplored. Existing autonomous drone systems are primarily designed for tracking single targets or human-made objects (Chen et al., 2018; Kline et al., 2023; Rohan et al., 2019). While drones can reliably track animals that have GPS tags (Kavwele et al., 2024), attaching tracking devices to protected species is often not permitted or practical. Approaches to autonomously track herds of livestock have been proposed (Luo et al., 2024), but any approach for wildlife must integrate ecological knowledge of the species and habitat to be effective. Wildlife tracking requires different approaches for group dynamics and collective movement, natural habitat features and obstacles, species-specific behaviours and reactions, and critical conservation and animal welfare considerations. These factors create unique challenges that existing autonomous systems cannot handle.

We present WildWing, an open-source autonomous drone system that tracks and records group-living animals' behaviours in semi-wild and wild environments, illustrated in Figure 1. We summarize WildWing's advantages compared with other approaches in Table 1. Our system allows users to integrate ecological knowledge into the

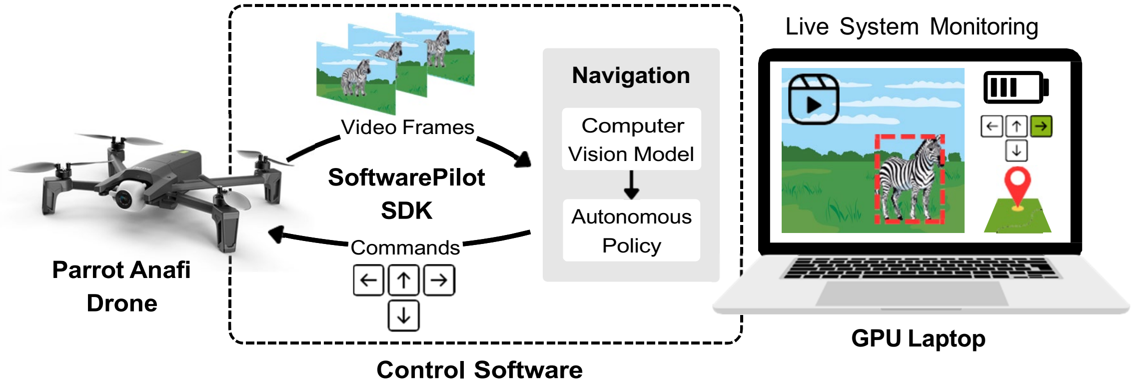

FIGURE 1 Overview of the WildWing Unmanned Aerial System (UAS) consisting of three components: A Parrot Anafi drone, open-source control software, and a laptop equipped with a GPU. The control software connects the drone to the autonomous navigation policy and allows users to monitor the system during deployment. The navigation policy analyzes video frames using computer vision models and determines the next commands to send to the drone. The control software is hosted on the laptop, where the users can also monitor the live WildWing system deployment.

navigation policies by tuning the system parameters, automatically maintaining optimal viewing positions while minimizing animal disturbance. By making the system both affordable ($650) and open-source, we aim to make autonomous behavioural data collection more accessible to researchers studying collective behaviour in natural settings. The WildWing system supports modular navigation policies, which users can build on and customize according to their use cases. We detail a novel autonomous navigation policy to track herds and record the behaviours of group-living animals.

2 | MATERIALS AND METHODS

The WildWing unmanned aerial system (UAS) consists of three main components: a Parrot Anafi drone, open-source control software and a laptop equipped with a GPU, illustrated in Figure 1. The control software monitors the drone's status, analyses the drone video stream and sends commands to the drone based on the chosen autonomous navigation policy. Our control software uses SoftwarePilot (Boubin & Stewart, 2020) as the software development kit (SDK) interface with the drone. The WildWing system may be customized by adjusting the navigation parameters to tailor the drone's approach for different species and populations. We summarize all tunable parameters in Table 3, along with the settings for our study. These parameters may be adjusted to customize the mission for wind conditions, species and habitat. The code to deploy the WildWing system and analyse the collected data is available on GitHub.

2.1 | Hardware

We selected hardware that is relatively inexpensive and widely available. We list alternative drones and laptop models in Table 2. The Parrot Anafi drone model was selected for its affordability and the SDK's ease of use. Parrot Anafi drones are no longer being produced, but refurbished versions can be purchased for $300 USD as of this publication date. Similar drone models include the DJI Mini 3, DJI Mavic 2 and Holybro X500 2 with PX4 Development Kit (DJI, 2024; Holybro, 2024). Note that the WildWing system will require some modification from the users to deploy on the DJI or Holybro SDK, but support for these drone models is currently under development. Comparable laptop models to the Lenovo Y530-15ICH include the Acer Nitro V 15 (ANV15-51-59MT) and Lenovo Legion Slim 5 Gen 8, both equipped with GPU (Buzzi, 2024).

2.1.1 | Parrot Anafi drone

The Parrot Anafi drone is a small, lightweight quadcopter model, weighing 320 grams and measuring 175 × 240 × 65 mm unfolded. The drone has a maximum battery life of 25 min with a maximum wind resistance of 50 km/h. The maximum horizontal and vertical speeds are 15 and 4 m/s, respectively. We used 4K ultra-high definition (UHD) mode to film the animals in 4K at 30 fps.

2.1.2 | Remote controller (RC)

The RC used in this system is the Parrot Skycontroller 3, which ships with the Parrot Anafi drone. Its maximum transmission range is four kilometres, and it live-streams video at a 720-pixel resolution. The RC communicates with the drone over a 2.4–5.8 GHz radio link and via a USB-C to USB-A cable with the computer.

2.1.3 | Laptop

SoftwarePilot requires a laptop running Ubuntu OS on x86 64 architecture. We used a Lenovo Legion Y530-15ICH with 16 GiB and an

TABLE 1 Comparison of animal monitoring methods.

Characteristic	Ground-based field observations (Altmann, 1974; Hughey et al., 2018)	Manually piloted drones (Dukowitz, 2024; Kholiavchenko et al., 2024; Koger et al., 2023)	Autonomous drones (livestock) (Luo et al., 2024)	WildWing
Data quality[a]	Limited by line of sight; partial group view	Full aerial view; group-level data; quality varies with pilot skill	Full aerial view; consistent quality for contained herds	Full aerial view; consistent quality for free-ranging groups
Initial cost[b]	Low ($1-2K for equipment)	Moderate ($2-5K for drone + training)	High ($10K+ for specialized systems)	Low ($650 for complete system)
Operating cost[c]	High (multiple field staff)	High (expert pilot $350/hr)	Low (automated operation)	Low (automated operation)
Data consistency[d]	Variable between observers; affected by fatigue	Variable between pilots; affected by skill level	Highly consistent within confined areas	Consistent across habitats and conditions
Reliability[e]	High for small areas; limited by observer	Moderate; affected by pilot availability	High in structured environments	High in varied environments
Spatial coverage[f]	Limited to accessible areas	Good coverage but limited by pilot skill	Limited to predefined areas	Adaptable to different habitats
Animal disturbance[g]	Moderate to high from human presence	Variable based on pilot skill	Low in habituated livestock	Minimized through predictable movements
Training required[h]	High (species expertise)	High (drone certification + expertise)	Moderate (system operation)	Moderate (system operation)
Data processing[i]	Manual processing; potential observer bias	Manual processing; varying quality	Automated processing	Automated processing optimized for behaviour analysis
Best use case	Individual behaviour; small groups	Occasional surveys; specific events	Regular monitoring of live-stock	Regular monitoring of wild animal groups

Note: Good performance; Medium performance; Poor performance.

[a]Data quality refers to the resolution, completeness, and usability of collected data for behavioural analysis. For computer vision applications, minimum pixel requirements vary by task: 50 × 50 px for species classification, 100 × 100 px for behaviour recognition, and 500 × 500 px for individual identification (Berger-Wolf et al., 2017; Kline, Kholiavchenko, et al., 2024).

[b]Initial costs include all equipment and training required to begin data collection. Ground-based costs primarily involve observation equipment, while drone-based methods require aircraft, controllers, and necessary certifications.

[c]Operating costs are calculated based on a typical 8-h field day, including personnel, equipment maintenance, and data processing time.

[d]Data consistency is measured by variation in quality and completeness of data across multiple collection sessions and between different operators.

[e]Reliability is assessed based on the successful data collection rate under various environmental conditions and technical constraints.

[f]Spatial coverage considers both the total area that can be monitored and the ability to follow moving groups across different terrain types.

[g]Animal disturbance is evaluated through behavioural changes, stress responses, and displacement from natural activities.

[h]Training requirements include both technical operation skills and domain knowledge needed for effective data collection.

[i]Data processing encompasses all post-collection steps needed to prepare data for analysis, including filtering, annotation, and quality control.

Intel Core i7-8750H CPU running Ubuntu 22.04.4 LTS, purchased for $350 USD. It is recommended to have at least 8 GB of RAM and 50GB of free disc space to store the data and run the computer vision models (Jocher et al., 2023).

2.2 | Control system

The control system manages the hardware, connects the drone to the autonomous navigation policy, detailed in Section 2.3, and allows users to monitor the system during deployment. The camera angle and degrees of movement of the drone are fixed to ensure consistent, high-quality footage for the duration of the flight. The camera gimbal is set to zero degrees, that is looking straight forward, so the viewing angle is consistent throughout the flight. The controller restricts its commands to moving the drone along one axis at a time to adjust the viewpoint incrementally. This way, we avoid drastic changes in the drone's viewpoint that could cause the animals to move out of frame. Minor, incremental adjustments also assist the system in avoiding manoeuvres requiring rapid acceleration, which are both noisy and deplete the battery quickly. The command to the drone includes moving left/right, up/down or forward/back. The user pre-sets the distance moved along each axis before the mission begins.

SoftwarePilot (Boubin & Stewart, 2020) is an open-source tool that allows users to connect drones with customizable Python scripts. This SDK provides an interface to the Parrot drone with

TABLE 2 Comparison of drone and laptop models that may be used with the WildWing system.

Hardware	Model	Cost (USD)
Drone	**Parrot Anafi with Skycontroller** (Refurbished)	**$300**
	DJI Mini 3	$445
	Holybro X500 v2 PX4 Development Kit	$508
	DJI Mavic 2 (Refurbishe)	$525
Laptop with GPU	**Lenovo Legion Y530-15ICH**	**$350**
	Acer Nitro V 15 (ANV15-51-59MT)	$800
	Lenovo Legion Slim 5 Gen 8	$1,200

Note: The drone and laptop used in testing are listed in bold (Buzzi, 2024; DJI, 2024; Holybro, 2024; Parrot, 2024).

access to the drone's telemetry and video streams and the ability to send commands to the drone. As illustrated in Figure 1, SoftwarePilot sends video frames from the drone to the laptop for processing and translates the commands from the controller to the drone. We provide users with a guide to getting started with SoftwarePilot.

The control software configures a live stream from the drone's camera accessed via RTSP protocol and displayed on the laptop using the VLC media player. The commands sent to the drone and the current battery level are also displayed. If the pilot detects a problem in the system, they may manually take over the controls at any time during the mission. The WildWing system continuously saves the computer vision model's output, allowing the pilot to oversee the operation and determine whether the animals were recognized. The computer vision model output, videos and telemetry information are automatically saved for each mission.

2.3 | Autonomous navigation policy

The WildWing control system is built to support modular autonomous navigation policies that can be used independently or combined to create specialized missions. Users can select the policy provided or customize it to match their research needs. This navigation approach enables broad usability and flexibility—users can tune the parameters of the navigation model appropriately based on their expert understanding of the species and habitat. The autonomous navigation model further integrates ecological understanding by defining the herd of animals in the scene as the object of interest.

For our deployment, we implemented the autonomous navigation policy to track group-living animals with drones proposed in Kline et al. (2023). This policy produced an 87% accuracy in navigating the drone compared to an expert pilot when tested in simulation on the KABR dataset (Kline, Kholiavchenko, et al., 2024). We use YOLOv5 (Jocher et al., 2023) computer vision model to detect, classify, and track the animals. YOLOv5su detected more animals in the frame than YOLOv8n and YOLOv8m in (Kline, Kholiavchenko, et al., 2024) so it was selected for this study. However, users can easily replace this YOLO model with newer versions, or any suitable object detector and classifier model.

We illustrate the navigation algorithm logic in Figure 3. This navigation approach builds on previous works using image-based tracking and detection for real-time control (Rohan et al., 2019; Venna et al., 2020), by extending this approach to track groups. The drone is programmed to move forward until the computer vision model detects the species of interest. Once the animals are detected, the centroid of the herd is calculated. Here, we define a *herd* as a collection of zebras within a circle of diameter 100 meters and that the circle is atleast 100 meters away from any other herd of zebras. The navigation model sends commands to the drone to keep the centroid of the herd within the center region of the drone's camera.

3 | WildWing FIELD DEPLOYMENT

We deployed the WildWing system at The Wilds, a 10,000-acre animal conservation centre in southeastern Ohio, USA (TheWilds, 2024). We obtained permission from The Wilds Science Committee to take field observations and fly drones in the pastures. The drone was flown within the pilot's visual line of sight, per US Federal Aviation Authority drone regulations. We used WildWing to collect behaviour video data of Grevy's zebras, giraffes and Przewalski's horses under the supervision of wildlife conservation experts. Before deploying the autonomous WildWing system, we flew several sessions manually on three different days over 3 months to gauge the animal's reactivity to the drone. We illustrate the WildWing deployment phases in Figure 2 and the corresponding navigation logic in Figure 3. We summarize the WildWing system settings in Table 3. Please refer to supplemental materials for additional details on the field deployment.

We summarize a selection of the data gathered during testing in Table 4. Sample images are included in Figure 4, and we include a comprehensive representation of the data collected in supplemental materials. The zebras and Przewalski's horses grazed near each other during the mission, allowing us to capture the entire herd. Giraffes, on the other hand, were more spread out across the pasture. We concentrated on two individuals standing close together and easily visible from our launch point. Our launch sites were nearer to the herds of zebras and giraffes than the Przewalski's horses. As a result, the approach time (refer to Step 5 in Figure 2) was shorter for zebras and giraffes than for the Przewalski's horses. Approach time is the duration between the initial launch and the first frame where the target species are detected.

The total frames with detections is the percentage of video frames that show detections from launch to the end of the mission. The approach time for the Przewalski's horses was proportionately longer than the other sessions, reducing the total of frames with detections. We also computed the percentage of usable video frames during the tracking phase only (Step 5), excluding the approach

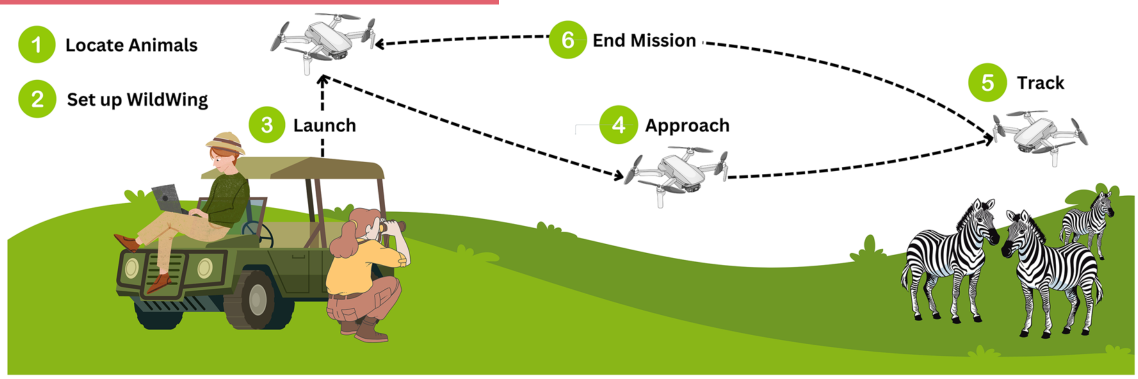

FIGURE 2 WildWing Deployment Phases. Steps 1 and 2 are accomplished manually. Steps 3–6 are accomplished autonomously by the WildWing system.

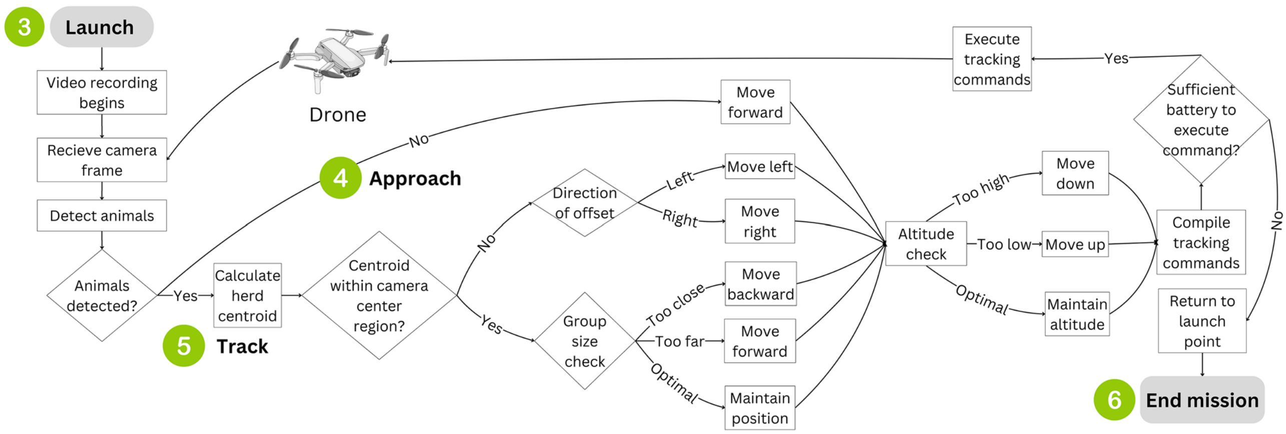

FIGURE 3 WildWing autonomous navigation policy for tracking herds. Components of the algorithm corresponding to each deployment phase in Figure 2 are labelled with numbers. Step 1, locating animals, and Step 2, set-up, are accomplished manually.

TABLE 3 WildWing system settings: flight and detection parameters.

Parameter	Value
Mission duration	200 s
Altitude	20 ± 3 m
Forward searching increment	10 m
Forward/back movement	5 m
Left/right movement	5 m
Up/down movement	5 m
Sampling rate	1:40 frames
Computer vision model	YOLOv5su

phase. Here, we define *usable frames* as those with adequate resolution to assess each animal's behaviour. The animals walked, grazed and stood still throughout the missions. Once the animals are detected by the WildWing system, the percentage of usable frames approaches nearly 100%.

We provide scripts to analyse the drone telemetry data collected during missions. Telemetry data includes timestamps, latitude, longitude, altitude, commands sent to the drone and the video frame used to determine the commands, as shown in Table 5. We provide a Jupyter notebook to calculate the speed and heading and to preview the drone's viewpoint from telemetry data.

4 | DISCUSSION

The deployment and evaluation of the WildWing system reveal both the potential and challenges of autonomous drone-based wildlife monitoring systems. While our field tests demonstrated promising results, several important factors influence the system's effectiveness across different contexts and conditions. Understanding these factors is crucial for both the current implementation and future deployments. Here, we discuss key considerations spanning system customization, environmental conditions and technical limitations that impact the broader applicability of drone-based monitoring approaches.

We observed that the animals at The Wilds did not exhibit high levels of reactivity or vigilance in response to the drone's approach. These animals are habituated to anthropogenic noise, as guests to the conservation centre often traverse through their pastures

TABLE 4 Summary of WildWing data collection.

Species	Animals captured[a]	Pasture size (acres)[b]	Video duration (sec)[c]	Approach time (sec)[d]
(a) Basic metrics				
Grevy's zebras	5/5	34	157	10
Giraffes	2/5	28	137	7
Przewalski's horses	8/8	50	139	72

Species	Total frames with detections[e]	Usable frames captured during track phase[f]	Behaviours recorded[g]
(b) Detection and behaviour metrics			
Grevy's zebras	86%	95%	Walking, Grazing
Giraffes	95%	98%	Walking, Standing
Przewalski's horses	43%	100%	Standing, Grazing

[a]Number of animals recorded during sampling out of total animals in pasture.
[b]Pasture area in acres.
[c]Total video length in seconds.
[d]Time spent searching for animals of interest (Step 4 in Figure 2).
[e]Percentage of frames with computer vision detections, from launch (Step 3) to mission end (Step 6).
[f]Percentage of frames with detections during the tracking phase only (Step 5), excluding the approach phase.
[g]Animal behaviours observed during the track phase (Step 5).

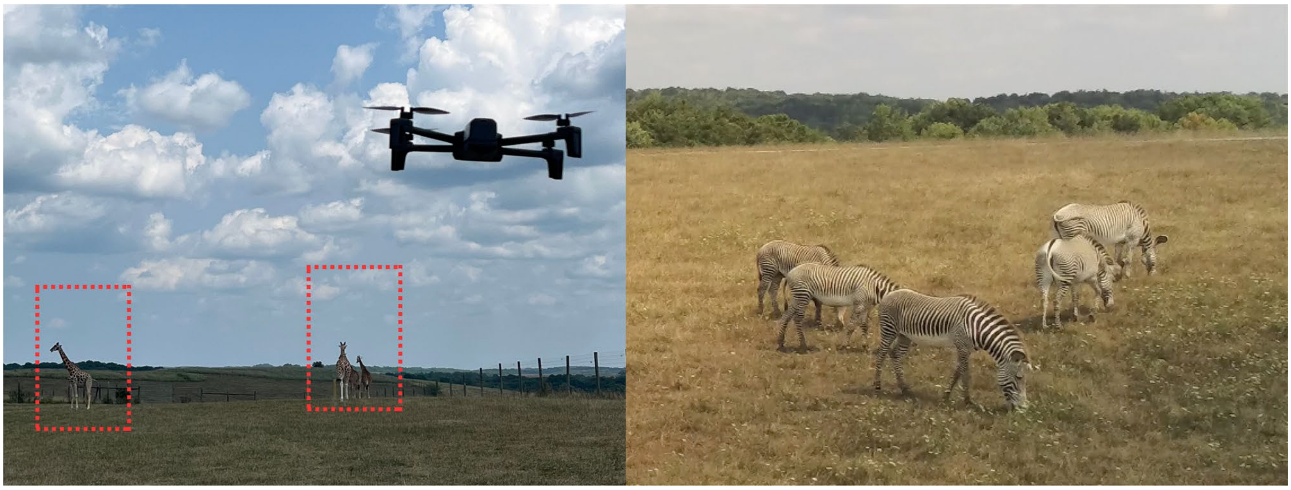

FIGURE 4 Left: Photograph of WildWing deployment (red bounding boxes added manually for visibility). Right: Photograph of Grevy's zebras collected with WildWing.

in buses and trucks. In addition, the animals have previously been exposed to drone noise, as The Wilds uses drones occasionally to locate and observe animals in pasture. Other animal populations may exhibit higher levels of vigilance in response to the presence of drones, especially if they experience lower background levels of anthropogenic noise (Schad & Fischer, 2023).

The low density of the animals on the landscape at The Wilds mimics the natural conditions from the KABR dataset, which was collected at Mpala Research Center in Kenya. However, other habitats may contain high densities of animals, particularly in areas where food and water are abundant and attract many other animals. High densities may increase instances where the model could incorrectly identify non-target species as if they were target species. As a result, herds may also become large, with fission–fusion events increasing in frequency, thus confusing the identity of herd members being followed. The WildWing navigation model may be adjusted to keep a maximum number of target animals in view to handle such scenarios. Around such resources, or in areas where population sizes of diverse species are large, tracking herds becomes challenging, depending on factors such as group size and spread, speed of movement, frequency of fission or fusion events and the degree of occlusion in the habitat. A comprehensive solution to these challenges is beyond the scope of this work, but we discuss potential solutions and research directions in Section 5.

The performance of the WildWing system is dependent on an accurate detection and classifi- cation model. YOLOv5 (Jocher

TABLE 5 Telemetry data collected by WildWing.

Telemetry		Description
Time stamp		YYYY-MM-DD HH:MM:SS
Location	Latitude	GPS
	Longitude	GPS
	Altitude	Meters
Command	*x*	Meters to move forward/back
	y	Meters to move left/right
	z	Meters to move up/down
Frame	jpg file	Video frame used to determine commands, with YOLO annotations

et al., 2023), which is trained on the COCO dataset, performed well on detecting zebras and giraffes, but struggled to accurately classify Przewalski's horses as horses, likely since this species was not included in the training dataset. YOLO models may be fine-tuned to increase performance on less common species and classify these animals more accu- rately. However, obtaining training sets with sufficient examples of rare or endangered species can be challenging. To solve this, we provide an option for a general animal category, using YOLO to inform the navigation decisions. The animals may be further classified by species after the mission concludes, either manually or by using a more general AI species classifier, such as BioClip (Stevens et al., 2024) or MegaDetector (Beery et al., n.d.). However, neither of these models were trained on drone imagery, so their applicability to the data produced by WildWing requires further investigation.

Weather conditions and habitat features are relevant factors that should be considered when deploying WildWing. During the field tests, the weather was 32°C (92°F), with 15 km/h wind speeds and 60% humidity. The Parrot Anafi drone is rated for temperatures between 14°C (6.8°F) and 40°C (104°F) and 93% humidity, and so operated successfully under these conditions. However, the laptop battery discharged faster than usual, likely due to the heat. The laptop battery typically lasts 4.5 h on a full charge but only lasts 3 h during field tests. We also note that Parrot drones are not designed for damp weather conditions. The zebra and giraffe pastures contained a few shade structures with no trees near the animals, allowing for unobstructed drone flights and straightforward deployment of the autonomous tracking system. However, since the Parrot Anafi drones lack automatic obstacle avoidance capabilities, deploying them in habitats with tall vegetation requires careful operation. We are developing support for DJI drones, which are equipped with obstacle avoidance features to enable safer operation in more complex environments.

5 | FUTURE DIRECTIONS

The development of autonomous drone systems for wildlife monitoring builds on recent advances in robotics and computer vision. As hardware costs decrease and navigation models improve, the coordinated deployment of multiple autonomous drones, or swarms, for ecological studies becomes increasingly feasible (Gruschak et al., 2024; Rolland et al., 2024). Multi-view data sets from swarms overcome the limited viewpoint of a single drone, allowing the system to handle larger groups, fission–fusion events, and fast-moving groups in complex habitats. Integration with existing sensor networks, including camera traps, acoustic sensors and GPS tags, can provide comprehensive ecosystem monitoring data (Besson et al., 2022). Edge computing enables efficient processing of the large volumes of data these systems generate (Kline, O'Quinn, et al., 2024).

Recent computer vision advances enable automated analysis of drone footage, including animal behaviour (Chan et al., 2025; Kholiavchenko et al., 2024), pose and movement (Koger et al., 2023; McNutt et al., 2024), and 3D modelling (Shukla et al., 2024). However, these vision models require extensive high-quality training data, which autonomous systems can help collect systematically. The development of quieter drones and optimal flight patterns that minimize noise disturbance is crucial, as anthropogenic noise can significantly impact animal behaviour and ecosystem dynamics (Afridi et al., 2024 ; Bennitt et al., 2019; Duporge et al., 2021; Mulero-P'azm'any et al., 2017). While the WildWing system currently focusses on specific species in semi-wild environments, its planned deployment in field conditions will test its broader applicability for behavioural ecology research. As these technologies mature, they can help address key questions about how animal movement patterns and social structures respond to environmental change, while generating the fine-grained, long-term data sets needed to understand ecosystem dynamics.

AUTHOR CONTRIBUTIONS

Jenna Kline conceived the idea of, designed and built the WildWing system, conducted field tests at The Wilds, and wrote the manuscript. Alison Zhong, Kevyn Irizarry and Jenna Kline contributed to the software development. Christopher V. Stewart provided expertise related to autonomous drones and control software. Charles V. Stewart provided expertise related to computer vision for the navigation component. Tanya Berger-Wolf advised the project and manuscript preparation and provided expertise related to Imageomics. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210X.70018.

DATA AVAILABILITY STATEMENT

All code is available on the project's GitHub repository, archived via https://doi.org/10.5281/zenodo.14902303 (Kline et al., 2025). Sample WildWing mission data, including video clips and drone telemetry, is available via https://doi.org/10.5281/zenodo.14838101 (Kline, 2025).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Supporting Information S1. WildWing deployment instructions.

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